HOT AREA TOPOGRAPHY

by

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Hot Area Topography

During the past two decades criminologists and criminal justice scholars have increasingly turned to spatial analysis as a vehicle to test criminological theory or to explore the efficacy of crime prevention efforts. The recent interest in the geography of crime has a number of sources. First, the National Institute of Justice (NIJ) drug market analysis program encouraged spatial analysis of drug markets as a means of study as well as a means of monitoring the effects of interventions (see ILJ, 1994 for an overview of the DMAP program). Second, the continued development of environmental criminology that links information about crimes to places and facilitates inquiries into the routine activities thesis and research questions tied to the situational crime prevention (examples of research in these traditions are found in Brantingham and Brantingham, 1981; Felson, 1994; Clarke, 1992). Finally, NIJ recent creation of the Crime Mapping Research Center seems destined to extend interest in spatial analysis of crime.

Recently, NIJ sponsored efforts have focused on the development of tools for spatial analysis of crime (see the locally initiated research partnership between NYPD and Hunter College). This paper builds on that effort by exploring the topography of Ahot areas@. Many of the statistics that are employed in spatial analysis make assumptions about the distribution of observations over space. For example density measures imply equal distribution of observations across the space, density gradients assume constant slope about centroids, and centrographic measures assume bivariate normal distributions or in some cases homoscedastic distribution of observations about a major axis (studies that use these methods include LeBeau, 1987; Langworthy and LeBeau, 1992; Langworthy and Jefferis, 1997; Levine, 1995; Levine, Kim and Nitz, 1995). Though many of these statistics are robust, departures from underlying assumptions should be determined and the effects discussed.

In this article assumptions underlying those statistics are explored graphically by examination of Baltimore County burglary hot area density plots. This form of analysis provides visualizations of hot area densities upon which to frame a discussion of the degree to which statistical assumptions are met. The focus is on assessing the topography of hot areas rather than on a substantive interpretation of clusters. Thus, what is required is the capacity to identify clusters, computer within cluster densities, and plot the resultant within hot area densities.

This analysis relied on STAC (see Block, 1993 for a description of STAC) to isolate hot burglary areas, LOCATE (a ring and sector counting program, program description attached) to provide counts of observations distributed in rings and sectors about the center of hot areas, and SYSTAT to plot the burglary densities of each hot area examined. The final product of the study is a series of graphic depictions of the topography of burglary densities within hot spots. These plots are used to draw conclusions about the distribution of burglaries within hot areas. This analysis focuses squarely on insights about spatial statistics--there is no effort to provide a substantive interpretation of the distribution of burglaries.

The Burglary Data

The data used in this study were drawn from a database provided by the Baltimore Co. Police Department to the National Institute of Justice in support of their intramural research project, AA Multi-method Exploration of Crime Hot Spots.@ Specifically, this project focused on the 6,219 burglaries for which there were valid AX@ and AY@ coordinates. These included 4,942 reported breaking and enterings, 629 attempted breaking and enterings, and 648 cleared breaking and enterings that occurred during the 13 month period between November 1, 1996 and November 30, 1997. As this project was concerned with within hot area topographic densities the only data drawn from the database were the AX@ and AY@ coordinate locations of completed, attempted and cleared breaking and enterings.

The Analytical Sequence

The study was conducted in three stages. First, STAC (Spatial and Temporal Analysis of CrimeCsoftware developed and distributed by the Illinois Criminal Justice Information Authority) was used to isolate hot burglary areas. STAC is well suited to this task as unlike many other clustering routines it isolates dense areas. STAC, using a 1,000 meter search radius,[1] isolated 9 hot areas depicted in Figure 1, the map of the Baltimore County Police Department jurisdiction. Table 1 presents the ellipse event counts. The 1,462 events within the hot areas constitute slightly less than 25 percent of the burglaries in the data set.

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[1]Different search radii would produce different hot spots.

Table 1. Baltimore County Burglary Hot Spots

Ellipse	Number of burglaries
1	375
2	262
3	92
4	242
5	118
6	108
7	106
8	91
9	68

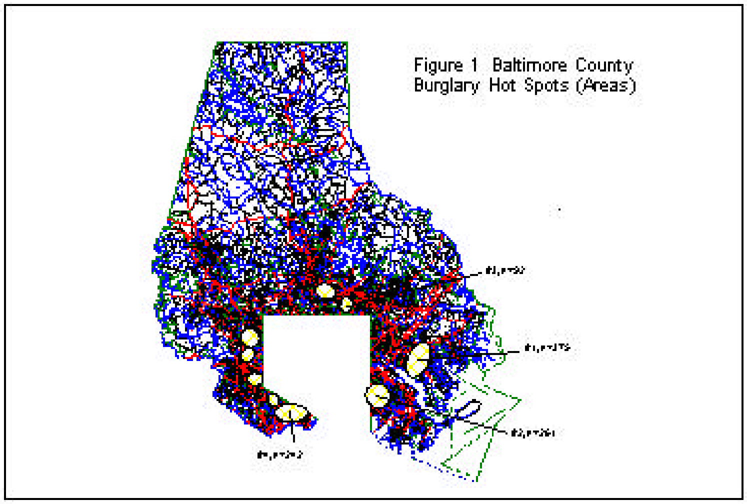


Figure 1 Baltimore County Burglary Hot Spots (Areas)

Second, four hot areas were selected for examination: the three with the greatest number of events and one smaller ellipse.[2] MapInfo was used to create the four data bases and export them as text files for input into LOCATE. LOCATE is a software program originally written in Fortran by Duane Marble, modified by Robert Wittick, and ported to DOS by James LeBeau. LOCATE is a program designed to count events into areas defined by user specified rings and sectors. For this exercise the concentric rings were specified at .005 longitude and latitude intervals; and, twelve sectors at 30 degree intervals were established. Table 2 presents the LOCATE output for each of the four ellipse that are the focus of this exercise.

[2]The only concern entering into the decision about selection of hot areas for examination was to choose several large ellipses with different shapes to see if shapes mattered and a smaller ellipse to see if scale mattered.

Table 2. RING AND SECTOR COUNTS FROM LOCATE

Ellipse 1, n=375

Ring Number	Sector number 1	2	3	4	5	6	7	8	9	10	11	12
1	3	2	1	3	2	1	1	3	0	0	1	3
2	5	0	1	2	9	11	4	1	4	3	4	18
3	18	1	1	6	15	35	11	5	9	14	8	29
4	17	15	12	5	3	18	23	2	17	2	5	9
5	9	0	1	0	0	0	1	2	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0

Ellipse 2, n=262

Ring number	Sector number 1	2	3	4	5	6	7	8	9	10	11	12
1	1	0	0	2	1	1	1	0	2	7	3	3
2	5	5	3	1	4	25	8	8	13	7	13	10
3	0	11	6	4	9	15	8	11	11	7	13	5
4	6	11	10	3	0	0	0	2	0	0	5	1
5	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0

Ellipse 3, n=92

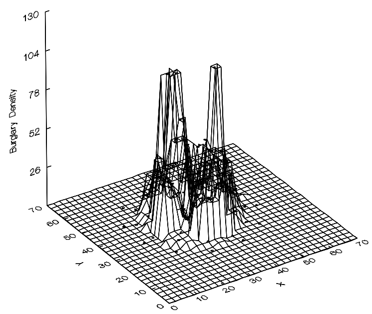
Ring number	Sector number 1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	3	2	1	2	3	6	2	0	0	2
2	1	2	3	3	3	16	1	12	3	0	7	13
3	3	2	1	0	0	0	0	0	0	0	0	1
4	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0

Ellipse 4, n=242

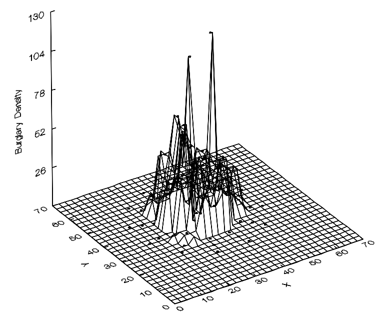
Ring number	Sector number 1	2	3	4	5	6	7	8	9	10	11	12
1	1	3	3	1	1	1	2	2	2	3	1	3
2	4	1	0	12	2	11	5	3	0	13	0	7
3	1	2	12	12	8	0	0	3	6	16	9	14
4	0	0	3	28	1	0	0	2	4	8	0	0
5	0	0	5	6	0	0	0	0	9	5	0	0
6	0	0	0	0	0	0	0	0	1	6	0	0

In the final stage of the study the ring and sector areal counts were converted to burglary densities and plotted using SYSTAT. The densities were computed by dividing the number of events in each ring/sector area by the area.[3] The resulting density was attached to the ring/sector area centroid producing a database composed of AX@ and AY@ coordinates and the burglary density in the AZ@ dimension. Finally, these data were plotted in SYSTAT producing the graphics attached as Figure 2.

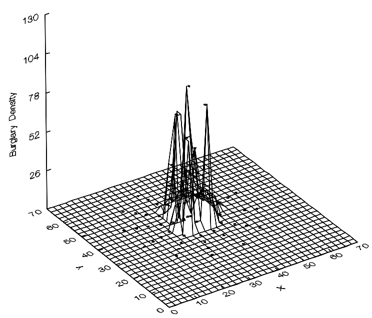
Figure 2. Ellipse Density Plots



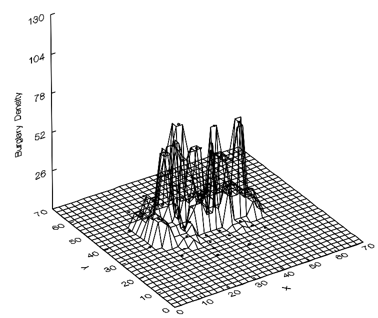
Ellipse 1



Ellipse 2



Ellipse 3



Ellipse 4

[3]Sector areas were computed by dividing ring areas by 12, the number of sectors per ring. Ring areas were computed by subtracting the area of the circle bounded by the inner boundary of the ring from the area of the circle bounded by the outer boundary of the ring.

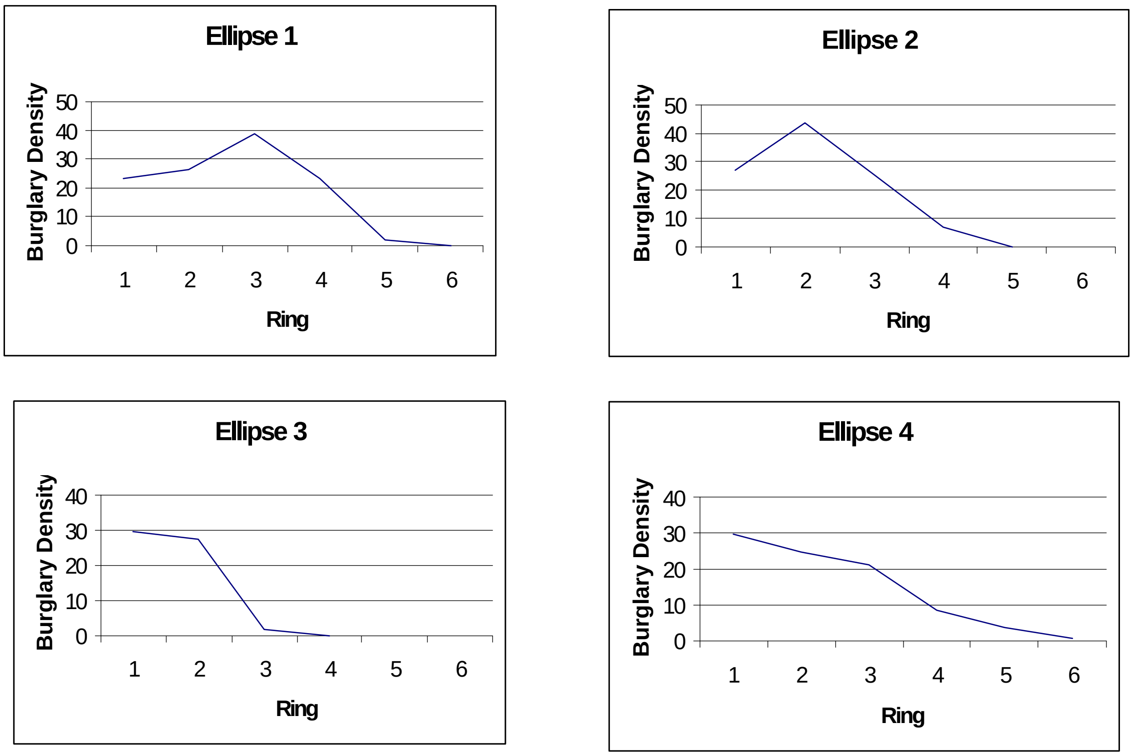
Discussion

Figure 2 presents evidence that uncritical use of hot area statistics may be misleading. Clearly, none of the ellipses suggests constant densities across the area of the ellipse. Indeed, there appears a great deal of within hot area variation as evidenced by the peaks and valleys apparent across the four examples.

Also, it is apparent that use of centrographic measures is problematic. The distribution of densities in these examples are, without exception, multi-modal. It is quite conceivable that the center of the hot area distribution is empty and the variance about the mean center as well as about the major and minor axes of the ellipses in not homoscedastic.

Finally, it seems apparent that density gradients also misrepresent the distribution of burglary densities. Figure 3 presents density gradients for each of the four ellipses that are the focus of this study. These gradients imply that the distribution is symmetrical about the mean center. Review of the distributions in Figure 2 suggests that this assumption is not warranted.

Figure 3. Ellipse Density Gradients



Conclusions

This paper uses ring and sector counts to explore the distribution of events within dense clusters. STAC was used to isolate dense clusters that were then examined to determine whether the assumptions that underlay spatial statistics that appear frequently in spatial analyses of crime are met. It is apparent that those assumptions cannot be taken for granted. Indeed the distributions do not exhibit a constant density that is important to the proper use of typical density statistics; the homoscedastic distribution assumption required to support interpretation of centrographic measures is not met; neither is distribution symetrical making interpretation of density gradients problematic.

On a positive note, this paper suggests that close examination of ring and sector data may provide information that will help us in the same manner that scatter-plots have supported two-dimensional data analysis. For example, the three dimensional plot of ellipse 1 suggests that the distribution is bi-modal. Had the STAC search parameter been set at 300 or 400 meters it is likely that two hot areas would have been isolated and each of them would have come much closer to meeting the symmetry assumptions that underlay many of our statistics.

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